Herbicide Reduction Through Targeted Weed Removal

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***Abstract*—Excessive use of herbicides in industrial farming contributes to significant environmental degradation, human health risks, and reduced agricultural efficiency due to the development of herbicide resistance. We present an autonomous weed detection and herbicide application system designed to reduce herbicide usage by 95% while maintaining crop yield. The system integrates advanced computer vision techniques such as Convolutional Neural Networks (CNNs) to accurately classify and localize weed infestations within crop fields in addition to providing a concise path for a flying agricultural vehicle to follow. By leveraging real-time image processing and machine learning models, the system provides precise herbicide application, reducing waste and minimizing environmental impact. Performance metrics such as weed detection accuracy, herbicide efficiency, and system robustness are evaluated against commercially-available and open-source alternatives. Future work will focus on optimizing the model for deployment on low-power edge devices and expanding the system's adaptability to different crops and environments.**

I. Introduction

The widespread use of herbicides in modern agriculture is a standard practice for controlling weeds and optimizing crop yields. However, the over-application of herbicides poses significant challenges, including environmental degradation, harmful effects on human health, and the emergence of herbicide-resistant weed species [1]. In 2020, the United States alone consumed approximately 256 thousand metric tons of herbicide, contributing to soil contamination, reduced biodiversity, and crop damage from non-targeted spraying [2]. In response to these growing concerns, precision agriculture and autonomous systems have emerged as potential solutions to improve herbicide efficiency and minimize environmental damage.

This project, titled "Herbicide Reduction Through Targeted Weed Removal," seeks to address these issues by developing an autonomous system that uses advanced computer vision and machine learning techniques to detect and neutralize weeds in real time. Our goal is to reduce herbicide usage by 95%, by identifying specific areas within fields that require treatment and applying herbicide only where necessary. This system integrates multiple subsystems, including weed detection using a vision-based model and an autonomous spraying mechanism to deliver the herbicide.

The focus of my contribution is the computer vision subsystem, which plays a critical role in classifying weeds and determining their locations within crop fields. We are evaluating several machine learning models, including Vision Transformers, classical Convolutional Neural Networks (CNNs), and pretrained ResNet architectures, to find the optimal solution for weed detection accuracy, computational efficiency, and real-time performance. This subsystem is a key component within the broader system architecture, providing the necessary data for the autonomous spraying subsystem to execute herbicide application.

In recent years, there has been significant research and development in the field of precision agriculture, particularly in the application of computer vision and machine learning for crop and weed classification. For example, John Deere's See & Spray™ system utilizes machine learning to detect and selectively spray weeds, resulting in substantial herbicide savings [3]. However, such commercial systems tend to be expensive and are primarily geared towards large-scale farming operations. Additionally, systems like FarmBot, which are open-source and designed for small-scale farming, offer mechanical weed removal but lack the scalability and herbicide application capabilities required for larger fields [4]. Our project aims to bridge this gap by offering a scalable, flexible, and cost-effective alternative that combines advanced machine learning with autonomous robotics.

The design of our computer vision subsystem draws heavily on techniques learned in courses such as Machine Learning, Deep Learning, and Computer Vision. These courses provided foundational knowledge in neural network architectures and image processing techniques, which are essential for building a robust weed detection model. Additionally, the integration of this subsystem into a real-world autonomous system aligns with principles learned in courses like Robot Controls and Unified Robotics, where the focus was on sensor fusion, motion planning, and system integration.

To achieve the goal of reducing herbicide use by 95%, several design requirements have been established for the computer vision subsystem:

- **Accuracy**: The system must achieve at least 95% accuracy in distinguishing weeds from crops, even under varying environmental conditions such as different lighting or plant occlusion.
- **Scalability**: The subsystem must be scalable to different farm sizes and crop types, with minimal degradation in performance when deployed in large fields.

- **Resource Efficiency**: The system must attempt to minimize computational and power requirements, making it suitable for deployment on a workstation laptop accessible to a farmer.

One major tradeoff for this project involve choosing between different machine learning architectures:

- **Classical CNNs**: Well-understood and computationally efficient but may lack the ability to capture complex spatial relationships in large crop fields.
- **Vision Transformers**: Capable of learning long-range dependencies within images, making them ideal for aerial imagery, but they are computationally expensive and may require more training data.
- **Pretrained ResNet models CITATION**: Offer a middle ground, leveraging transfer learning to achieve high accuracy with less training data, but they may require significant fine-tuning.

II. Methodology

In this project, we developed and evaluated three machine learning models for weed detection and herbicide application: a classical Convolutional Neural Network (CNN), a pretrained ResNet, and a Vision Transformer. The primary goal of this methodology was to determine the optimal model architecture that meets the design requirements of high accuracy, real-time processing, and scalability. This section describes the data preparation, model training and evaluation processes, as well as the parameter optimization techniques used to fine-tune each model.

A. Dataset Preparation

We utilized the *Agriculture-Vision* dataset, which contains 21,061 aerial farmland images in both RGB and near-infrared (NIR) formats, annotated with boundaries and masks that indicate various field anomalies such as weed clusters CITATION. Data preprocessing involved several key steps:

- **Image Rescaling**: All images were rescaled to a fixed resolution of 512x512 pixels to ensure consistency across different models.
- **Data Augmentation**: We applied data augmentation techniques such as random cropping, horizontal and vertical flipping, rotation, and brightness adjustments to artificially increase the size of the training dataset and improve model generalization.
- **Train-Test Split**: The dataset was split into training, validation, and test sets with a ratio of 70:15:15. Stratified sampling was used to ensure a balanced distribution of classes (weeds, crops, and background) across the sets.

B. Model Architectures

1) **Convolutional Neural Network (CNN)**:
    - A classical CNN architecture was implemented using several convolutional layers, each followed by ReLU activation and max-pooling layers. The model was designed with a small number of parameters to ensure real-time performance on edge devices.
    - The CNN was trained using the Adam optimizer with an initial learning rate of 0.001, and batch normalization was applied to improve convergence.

2) **Pretrained ResNet**:
    - A ResNet-50 architecture pretrained on the ImageNet dataset was fine-tuned for the task of weed detection. The final fully connected layer was replaced with a softmax classifier with three output classes (weeds, crops, and background).
    - We employed transfer learning techniques, freezing the lower convolutional layers initially and fine-tuning only the top layers. Gradually, we unfroze more layers and trained the entire model with a reduced learning rate of 0.0001.

3) **Vision Transformer**:
    - The Vision Transformer (ViT) was employed due to its ability to capture long-range dependencies within images, which is useful for detecting large weed clusters in aerial imagery.
    - The ViT was trained from scratch using the same training set, with an initial learning rate of 0.0001 and a weight decay of 0.01. Attention heads and hidden layer dimensions were varied to find the optimal model configuration.

C. Hyperparameter Tuning

For each model, we conducted hyperparameter tuning using grid search and random search techniques. The following hyperparameters were varied:

- **Learning Rate**: Tested learning rates ranging from 1e-5 to 1e-2 to find the optimal balance between fast convergence and stable training.
- **Batch Size**: Batch sizes of 16, 32, and 64 were tested to optimize memory usage and model performance.
- **Number of Layers**: For the CNN, the number of convolutional layers was varied between 4 and 8 to determine the trade-off between model complexity and inference speed.
- **Dropout Rate**: Dropout rates ranging from 0.1 to 0.5 were tested to reduce overfitting in all models.

D. Model Evaluation

Each model was evaluated based on several performance metrics:

- **Accuracy**: The percentage of correctly classified areas of the field (weeds, crops, and background).
- **Precision and Recall**: For each class, precision and recall were calculated to evaluate the model's ability to correctly classify weeds and avoid false positives.
- **F1-Score**: A weighted average of precision and recall to provide a more balanced view of the model's performance.
- **Inference Time**: The time taken to process each image, ensuring that the model can operate in real time, although

this is a less important metric than the accuracy-related scores.

- **Power Consumption**: For future deployment on edge devices, power consumption was measured to ensure that the models could be implemented within the hardware constraints.

E. Experiments

1) **Baseline Performance**:
   - Each model was trained on the full dataset and its baseline performance was evaluated on the test set.
2) **Parameter Sweeps**:
   - For each model, parameter sweeps were conducted by varying key hyperparameters (learning rate, batch size, number of layers) to identify the optimal settings.
3) **Ablation Studies**:
   - We conducted ablation studies to assess the importance of each model component. For the CNN, we removed certain layers to analyze their contribution to accuracy. For the Vision Transformer, we varied the number of attention heads to evaluate their impact on performance.

F. Conclusion

The development of an autonomous system for weed detection and targeted herbicide application has the potential to significantly reduce the environmental and health impacts of herbicide overuse in industrial farming. By integrating advanced computer vision techniques with autonomous spraying mechanisms, this system aims to reduce herbicide use by up to 95%, promoting more sustainable and efficient farming practices. The methodology we have outlined—comparing different machine learning architectures such as Convolutional Neural Networks (CNNs), pretrained ResNet models, and Vision Transformers—serves as a foundation for selecting the optimal model that balances accuracy, real-time performance, and scalability. The implications of this work extend beyond simply reducing herbicide usage. A more precise, resource-efficient system could improve crop yields, reduce soil degradation, and mitigate the development of herbicide-resistant weeds, contributing to the long-term sustainability of agricultural ecosystems. Moreover, by making this system adaptable to various farm sizes and conditions, it has the potential to democratize precision agriculture, making advanced farming technologies accessible to small- and medium-scale farmers who may otherwise be unable to afford existing large-scale commercial solutions.

Despite the promising potential of this approach, several areas require further study. First, while we have outlined methods to evaluate model performance under real-time conditions, the system must be rigorously tested in real-world environments to ensure its robustness across varying field conditions, such as changing light, occlusion, and plant density. Additionally, while the computational efficiency of the models is an important factor for edge deployment, power consumption, and hardware optimization need further exploration to ensure feasibility in large-scale operations. Future work could also explore the integration of multispectral imagery to enhance the system's ability to differentiate between crops and weeds, even in more challenging conditions. Furthermore, incorporating adaptive learning techniques could enable the system to improve over time by continuously updating its model based on new data collected in the field.

In conclusion, the methods and models outlined in this work lay the groundwork for a robust and scalable weed detection system with the potential for significant environmental and economic benefits. As the project progresses, we will focus on further optimizing the system for real-world deployment and evaluating its effectiveness under practical conditions, paving the way for smarter, more sustainable farming practices.

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